# Neural Learning of Predicting Driving Environment

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***Abstract*— Vehicle power management has been an active research area in the past decade, and has intensified recently by the emergence of hybrid electric vehicle technologies. Research has shown that driving style and environment have strong influence over fuel consumption and emissions. In order to incorporate this type of knowledge into vehicle power management, an intelligent system has to be developed to predict the current traffic conditions. This paper presents our research in neural learning for predicting the driving environment. We developed a prediction model, an effective set of features to characterize different types of roadways, and a neural network trained for online prediction of roadway types and traffic congestion levels. This prediction model was then used in conjunction with a power management strategy in a conventional (non-hybrid) vehicle. The benefits of having the predicted drive cycle available are demonstrated through simulation.**

## I. Introduction

DRIVING patterns exhibited in a real world driver are the product of the instantaneous decisions of the driver to cope with the (physical) driving environment. Research has shown that driving style and environment have strong influence over fuel consumption and emissions [1, 2]. Specifically road type and traffic conditions, driving trend, driving style, and vehicle operation modes have various degrees of impacts on vehicle fuel consumptions. However most of the existing vehicle power control approaches do not incorporate the knowledge about driving patterns into their vehicle power management strategies. Only recently has the research community in intelligent vehicle power control began to explore the ways to incorporate the knowledge about online driving patterns into online control strategies [3, 4, 5, 6]. A comprehensive overview of intelligent systems approaches for vehicle power management can be found in [7].

One critical part of this research is the development of an intelligent system that can accurately predict the driving patterns in the near future. This paper presents our research related to the development of a neural network system for the prediction of roadway type and traffic congestions. We developed innovative techniques to model the road environment of a driving trip, select features that effectively characterize roadway type and traffic congestion levels, and a neural network that is trained for online prediction of roadway type and traffic congestion level in the near future during a driving trip.

This paper is organized as follows. Section II presents an intelligent system model for the prediction of roadway type and traffic congestion level, Section III presents the neural network we developed, Section IV presents the intelligent vehicle power management system that uses the neural network for online roadway prediction and its performances on three standard driving cycles and Section V concludes the paper.

## II. Predicting Roadtype and Traffic Congestion Level

We model the road environment of a driving trip as a sequence of different road types such as local, freeway, arterial/collector, etc. augmented with different traffic congestion levels. A set of 11 standard drive cycles, called facility-specific(FS) cycles, to represent passenger car and light truck operations over a range of facilities and congestion levels in urban areas was developed by the research center in [8, 9]. The 11 drive cycles can be divided into four categories, freeway, freeway ramp, arterial, and local. More recently the data of FS cycles [9] have been updated to reflect the speed limit changes in the freeway category. In the model used, the two categories, freeway and arterial are further divided into subcategories based on a qualitative measure called level of service (LOS) that describe operational conditions within a traffic stream based on speed and travel time, freedom to maneuver, traffic interruptions, comfort, and convenience. Six types of LOS are defined with labels, A through F, with LOS A representing the best operating conditions and LOS F the worst. Each level of service represents a range of operating conditions and the driver's perception of those conditions; however safety is not included in the measures that establish service levels [9, 10]. For the convenience of description we label the 11 classes of roadway types and congestion level as R[1], …., R[11]. Table 1 shows the most recent definition of these road types in [9] along with the labels we assigned.

We formulate the problem of roadway type prediction as follows. Let SP[t] be the speed profile of a driver on the road, $t = 0, 1, \ldots, t_c$, where $t_c$ is the current time instance, and RT[t] be the roadway types the driver needs to go through to complete his trip, where $0 < t < t_e$ , $t_e$ is the time when the trip ended. At any given time $t_c$, $RT(t_c) \in \{ R[i] \mid i = 1, \ldots,$

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14. ABSTRACT
**Abstract Vehicle power management has been an active research area in the past decade, and has intensified recently by the emergence of hybrid electric vehicle technologies. Research has shown that driving style and environment have strong influence over fuel consumption and emissions. In order to incorporate this type of knowledge into vehicle power management, an intelligent system has to be developed to predict the current traffic conditions. This paper presents our research in neural learning for predicting the driving environment. We developed a prediction model, an effective set of features to characterize different types of roadways, and a neural network trained for online prediction of roadway types and traffic congestion levels. This prediction model was then used in conjunction with a power management strategy in a conventional (non-hybrid) vehicle. The benefits of having the predicted drive cycle available are demonstrated through simulation.**

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TABLE I.
STATISTICS OF 11 FACILITY SPECIFIC DRIVING CYCLES [9]

| Facility Cycles | | | | |
|---|---|---|---|---|
| **Cycle** | **$V_{avg}$ (mph)** | **$V_{max}$ (mph)** | **$A_{max}$ (mph/s$^2$)** | **Length (sec)** |
| **Freeway LOS A: R[1]** | 67.79 | 79.52 | 2.3 | 399 |
| **Freeway LOS B: R[2]** | 66.91 | 78.34 | 2.9 | 366 |
| **Freeway LOS C: R[3]** | 66.54 | 78.74 | 3.4 | 448 |
| **Freeway LOS D: R[4]** | 65.25 | 77.56 | 2.9 | 433 |
| **Freeway LOS E: R[5]** | 57.2 | 74.43 | 4.0 | 471 |
| **Freeway LOS F: R[6]** | 32.63 | 63.85 | 4.0 | 536 |
| **Freeway Ramps: R[7]** | 34.6 | 60.2 | 5.7 | 266 |
| **Arterials LOS A-B: R[8]** | 24.8 | 58.9 | 5.0 | 737 |
| **Arterials LOS C-D: R[9]** | 19.2 | 49.5 | 5.7 | 629 |
| **Arterials LOS E-F: R[10]** | 11.6 | 39.9 | 5.8 | 504 |
| **Local Roadways: R[11]** | 12.9 | 38.3 | 3.7 | 525 |

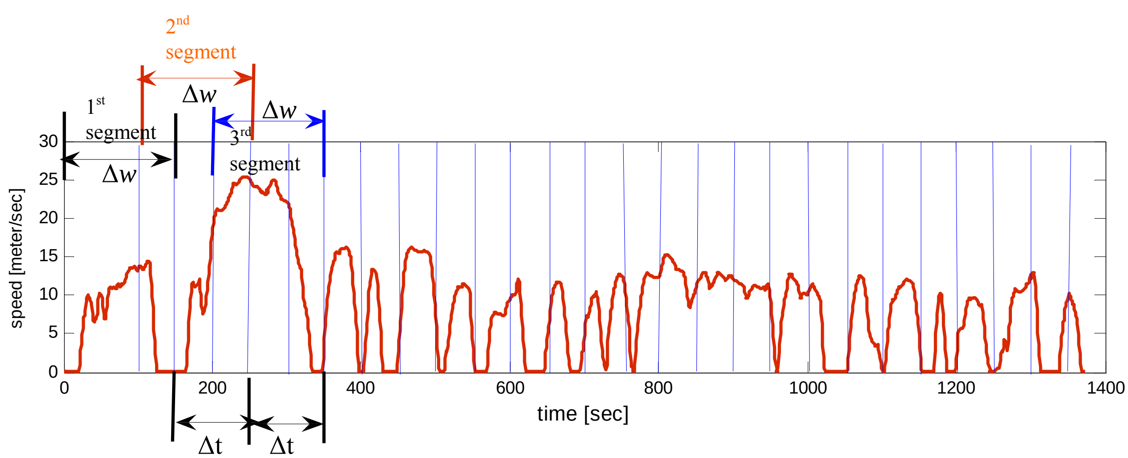



Figure 1. Illustration of segments of a speed profile. The X axis represents time measured in seconds, and the Y axis represents speed measured in meters per second.

11}. The roadway type in the near future needs to be predicted based on the short term history of the driver during the trip.

Specifically, we attempt to develop a non-linear function F such that F(SP(t)|t $\in [(t_c - \omega), t_c])$ = R[j], 0< j $\leq$ 11, where $\omega$>0 is called window size that characterizes the length of the speed profile that should be used to explore driving patterns. The variable R[j] is the roadway type the driver will be on during the time interval [$t_c$, ($t_c$+$\Delta t$)], i.e. RT[t] = R[j] for t $\in$ [$t_c$, ($t_c$+$\Delta t$)]. We refer to $\Delta t$ > 1 as the time step. To solve this problem we need to determine four different aspects of the roadway type predictor:

- select effective features that can be extracted from SP(t), $t_c - \omega < t \leq t_c$ for the prediction of the current roadway type.
- determine the optimal window size $\omega$
- determine the optimal time step $\Delta t$
- develop a function F that has the capability of accurately predicting roadway types in sufficiently short time suitable for online driving prediction. In this paper F is a neural network described in the next section.

## III. Developing a Neural Network to Predict Road Types and Traffic Congestion Levels

In this section we describe how we developed the four aspects listed for predicting road types and traffic congestion levels.

### A. Feature Selection

Roadway types and traffic congestion levels can be observed generally in the speed profile of the vehicle. The statistics used to characterize driving patterns include 16 groups of parameters (62 total) suggested by the driving model used in [9], and parameters in 9 out of these 16 groups critically affect fuel usage and emissions. However it may not be necessary to use all these features for

predicting a specific drive pattern and additionally new features may be explored as well. For example in [5], Langari and Won used only 40 of the 62 parameters and then added seven new parameters: trip time, trip distance, maximum speed; maximum acceleration; maximum deceleration; number of stops, idle time (percent of time at speed 0 km/h). However, the use of additional parameters needs to be balanced with the "curse of dimensionality": too many features may degrade system performance. Furthermore, in onboard vehicle implementation more features imply higher hardware cost and/or more computational time. The problem of selecting a subset of optimal features is a classic research topic in pattern recognition and a NP problem. Because the feature selection problem is computationally expensive, research has focused on finding a quasi optimal subset of features, where *quasi optimal* implies good classification performance, but not necessarily the best classification performance. Interesting feature selection techniques can be found in [11, 12, 13]. However most of these feature selection algorithms were developed for 2-class classification problem, and extensions to K-class (K>2) will significantly increase the computational time. With this background in mind, we developed the following feature selection algorithm based on roadway types.

*Feature selection algorithm*

Step 1: Let X be the training data set, and $\Omega$ be the initial set of n features, which can be obtained from those suggested by the research community, as discussed earlier.

Step 2: Re-labeling data in X with freeway samples as “1” and all others as “0”. Denote this training data set as X1. Select the best features from $\Omega$ that can classify all the freeway data against all other data in X1. Denote this feature set as F1.

Step 3: Re-labeling data in X with freeway ramp samples as “1” and all others as “0”. Denote this training data set as X2. Select the best features from $\Omega$ that are NOT in F1 and that can classify all the freeway Ramp data against all other data in X2. Denote this feature set as F2.

Step 4: Re-labeling data in X with Arterial data samples as “1” and all others as “0”. Denote this training data set as X3. Select the features that are NOT in $F1 \cup F2$ and can best classify all the Arterial data against all other data in X3. Denote this feature set as F3.

Step 5: Re-labeling data in X with local roadway data samples as “1” and all others as “0”. Denote this training data set as X4. Select the features that are NOT in $F1 \cup F2 \cup F3$ and can best classify all the local roadway data against all others in X4. Denote this feature set as F4.

Step 6: Output feature set F = $F1 \cup F2 \cup F3 \cup F4$

When the algorithm described above was applied to an initial set ($\Omega$) of 47 features suggested by Langari and Won in [5], we obtained the set (F) of 14 features shown in Table II.

TABLE II.
14 FEATURES SELECTED FOR ROADWAY TYPE PREDICTION

| Name of selected features: |
|---|
| Trip distance; |
| Maximum speed; |
| Maximum acceleration; |
| Maximum deceleration |
| Average speed |
| Average acceleration |
| S. D. of acceleration |
| Average deceleration |
| % of time in speed interval 0-15 km/h |
| % of time in speed interval 15-30 km/h |
| % of time in speed interval >110 km/h |
| % of time in deceleration interval (-10)-(-2.5) m/s2 |
| % of time in deceleration interval (-2.5)-(-1.5) m/s2 |
| Number of acceleration/deceleration shifts per 100m where the difference between adjacent local max-speed and min-speed was >2 km/h |

*B. Optimal Window Size and Time Step in Online Predicting*

Since we are trying to predict the road type in the near future, the driving speed in the last segment, [$t_c - \Delta w$, $t_c$], where $t_c$ is the current time, is used to predict the road type the driver is on during time period, [$t_c$, $t_c + \Delta t$]. The prediction is made at time steps, k$\Delta t$, k = 1, 2, …. The window size of the speed profile segments is $\Delta w$, where $\Delta w$>0. The time interval over which the prediction is made is $\Delta t$. Figure 1 illustrates these two parameters on the speed profile of the UDDS (Urban Dynamometer Driving Schedule) drive cycle. The x-axis represents the time during a driving cycle and y-axis represents the vehicle speed in meters per second. The segments shown have the equal size of $\Delta w$ = 150 seconds and the time step, $\Delta t$ = 100 seconds. Please note that $\Delta t$ = 100 seconds is chosen here only for the clarity of the illustration. In reality, as we will show, $\Delta t$ should be smaller than 100 seconds. The two parameters are important for the accuracy of prediction. Since features characterizing road types are extracted from the speed profile of the vehicle in the time interval [$t_c - \Delta w$, $t_c$], if $\Delta w$ is too small, the segment may be too small to contain useful information. If $\Delta w$ is too big, the segment may contain obsolete information. Once $\Delta w$ is determined, the 14 features presented in Table 2 are extracted from the speed profile within the time interval [$t_c - \Delta w$, $t_c$] and used as the input feature vector to the neural network described in the next section. The time step $\Delta t$ also needs to be properly determined. If $\Delta t$ is too short, it would imply that the prediction routine would run often. If it is too long, the

roadway type may change during the near future horizon, [$t_c$, $t_c + \Delta t$ ].

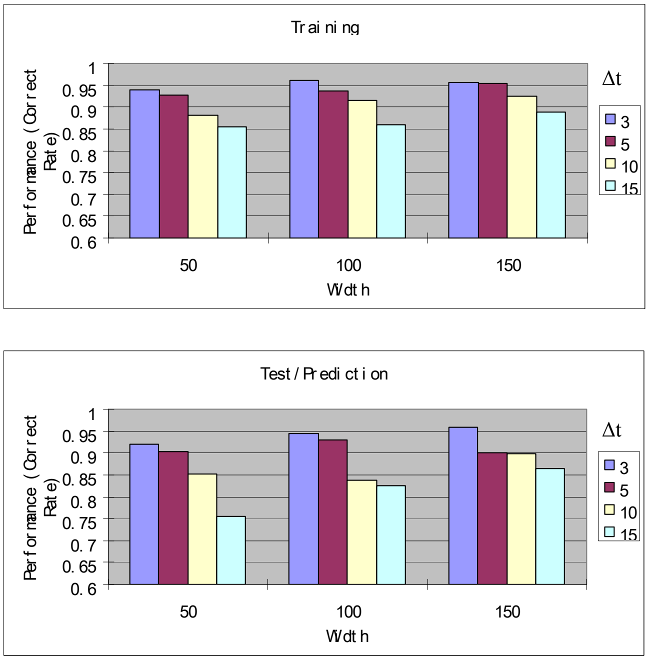



Figure 2. Prediction accuracies from various window sizes and time steps.

The optimal window size and optimal time step are determined through a series of experiments by varying $\Delta w$ in a reasonable range such as 50, 100, 150, and $\Delta t = 3$ seconds, 5 seconds, 10 seconds, 15 seconds. For every pair of window size and time step, a neural network system is trained (see detail in the next section) and tested on data sets extracted from the 11 drive cycles provided in [14] the software library.

Figure 2 shows the results of this experiment. Based on the analysis of the performances on both the training and test data, it appears that the performances between $\Delta w$=100 seconds and $\Delta w$ = 150 are very close, so either one should work well. It appears that $\Delta t = 3$ seconds since this time step works well on all window sizes. We want to point out that $\Delta t = 1$, or 2 seconds worked equally well. Since $\Delta t = 3$ implies less frequent prediction, this is the time step we select.

### *C. Training a neural network to predict road types*

We developed a multi-layered, multi-class neural network, NN_RT&TC, for the prediction of road types and traffic congestion levels. The training data are obtained as follow. We segmented and labeled all 11 drive cycles in [14], UDDS, HWFET, US06, SC03, LA92, IM240, Rep05, NY City, HL07, Unif01, Arb02 for use as training and test data. The simulation software in [14] is a "forward-looking" model that simulates fuel economy and performance in a realistic manner — taking into account transient behavior and control system characteristics. It can simulate an unrivaled number of predefined configurations (conventional, electric, fuel cell, series hybrid, parallel hybrid, and power split hybrid). In this research project we use the "forward-looking" model software in [14] to simulate all facility specific drive cycles to generate numerical data such as fuel consumption and emissions, and vehicle performance, etc. Each of the 11 drive cycles can be considered as a composite of the 11 classes of roadway types and traffic congestion levels. Figure 3 shows an example of a labeled drive cycle, LA92 segmented according to the definition of the 11 classes as defined in [9]. The X axis indicates the time and the Y axis indicates the speed in meters/second.

For a window size, $\Delta w$, time step, $\Delta t$, and a driving cycle DC(t) ($0 \le t \le t_e$), we generate DC segments on intervals, $s_0 = [t_0, \Delta w)$, …, $s_k = [k\Delta t, \Delta w + k\Delta t)$, … $s_{ke} = [t_e - \Delta w, t_e]$, where $k \ge 1$.

From the speed function of each segment, we extract a vector of the 14 features specified in Table I. The feature vectors are randomly sampled into training and test data with a ratio of 4:1. For example, for $\Delta w$ = 50 seconds, $\Delta t$ =3 seconds, we obtained a training data set of 2758 data samples, and a test set of 689 data samples. The feature vector extracted from every speed signal segment is labeled by the roadway type of its next segment since we are training the prediction function.

A multi-class neural network, NN_RT&TC, of 14 input nodes and 11 output nodes with a hidden layer of 20 nodes has been trained for the roadway type prediction. The output nodes correspond to the 11 class labels, {R[1], …, R[11]}. The neural network is trained using the one-against-all scheme [15].

Based on the study results presented in the last section, we use $\Delta w$=150 seconds, $\Delta t$ = 3 seconds. The training and test data are generated from 11 data in [9] and 11 driving cycles in [14]. There are totally 4399 segments generated from these 22 driving cycles. From each segment a vector of 14 features (see Table 2) is extracted. The separation of training and test data is through a random stratified sampling procedure. As the result the training data contain 3777 feature vectors and the test data contain 622 feature vectors. The performance of the neural network is 95.87% on the training data and 95.18% on the test data.

When NN_RT&TC is used inside a vehicle to predict the roadway type at time $t_c$, the vector of the 14 features is extracted from the vehicle speed during the time interval, [$t_c$-150seconds, $t_c$]. The output from NN_RT&TC is the roadway type to be used by an intelligent vehicle power management to produce the optimal power distribution during time interval [$t_c$, $t_c$ +3seconds]. Its online performance is discussed in the next section.

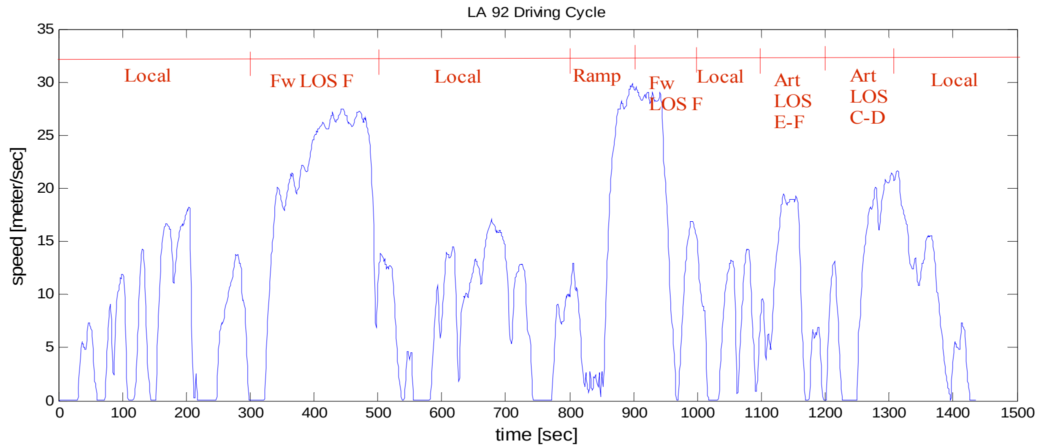



Figure 3: An example of labeled driving cycle, LA92. X axis represents time measured in seconds, the Y axis represents speed measured in meter/second.

## IV. APPLICATION IN VEHICLE POWER MANAGEMENT

The neural network described in section III, NN_RT&TC, has been fully integrated into an intelligent vehicle power management system, which will be called ***IPC*** [intelligent power controller]. Figure 4 shows the key components of the system. The vehicle system sends signals at time t such as the vehicle speed, v(t), the power required at the driveline, $p_d(t)$, and the power required by the electric loads, $p_l(t)$ to the ***IPC***. The ***IPC*** has three major components: NN_RT&TC, Knowledge Base, and Intelligent Controller.

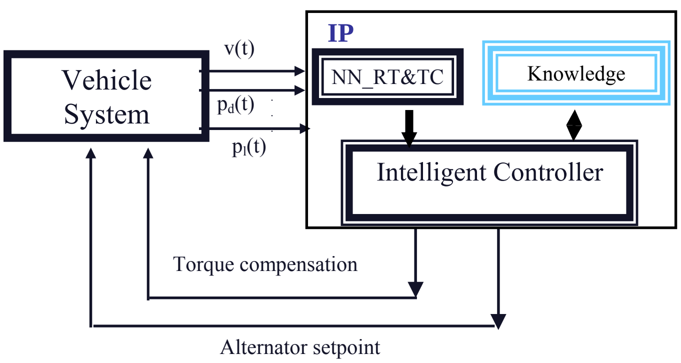



Figure 4. *IPC*, an intelligent vehicle power controller that incorporates the knowledge about the road type and traffic congestion level predicted by a neural network into power management decisions.

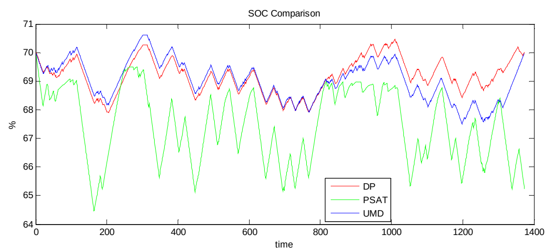
The NN_RT&TC is the neural network we presented in the last section. The knowledge base contains the knowledge about the optimal alternator setpoint and torque compensation learned from the 11 drive cycles in [9]. Based on the prediction of the roadway type and traffic congestion level made by NN_RT&TC, vehicle system information, and the stored knowledge related to the predicted roadway type, the Intelligent Controller outputs the optimal setting of torque compensation and alternator setpoint for the vehicle system to use during time interval, $[t, t+\Delta t]$.

We have implemented the ***IPC*** in simulation using a conventional vehicle model in [14] simulation software. The vehicle model is a commercial vehicle with a 95KW 1.9L liter Spark Ignition engine, 5 gear manual transmission and a 12-14V 1.5 KW alternator, and a 66Ah/12V lead acid battery. Experimental results for three driving cycles, UDDS, LA92 and UNIF01, are shown in Figure 5 and Table 3. UDDS is also sometimes called FTP72. The cycle represents city driving conditions in a urban area with frequent stops. LA92 (also called Unified cycle) was constructed of segments of actual driving recording in Los Angeles. It is a more aggressive driving cycle than the FTP (Federal Test Procedure). It has higher speeds, higher accelerations, fewer stops per mile, and less idle time. The UNIF01 Cycle was developed for the California Air Resources Board [9] and is a modified form of the LA92. For the purpose of comparison we have used off-line Dynamic Programming (DP) to find the optimal operating points [16,17]. Since the DP algorithm requires full knowledge of the entire driving cycle to optimize the power management strategy, it is not applicable to online control. However the results generated by DP can be used as a benchmark for the performance of power control strategies. In Figure 5, we show the battery state of charge (SOC) for three different drive cycles using three different drive cycle prediction and control algorithms. The red lines in the plots show the SOC when DP is used for optimal prediction and control (with full drive cycle knowledge). The green lines show the SOC generated using the existing control strategy with no drive cycle prediction [14]. Finally, the blue lines show the results when the ***IPC*** prediction and control routine is used as described above.

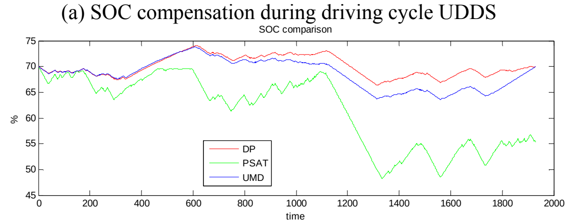
It can be observed that the SOC curves generated by the ***IPC*** for each drive cycle have similar behavior to the respective ones generated by the offline DP algorithm. The SOC curves generated by the controller [14], on the other hand, are significantly different from the optimal curves.

Table III presents the performance comparison with respect to fuel consumption. We use the fuel consumed by the simulation vehicle with the conventional power management controller as the baseline [14]. For the UDDS

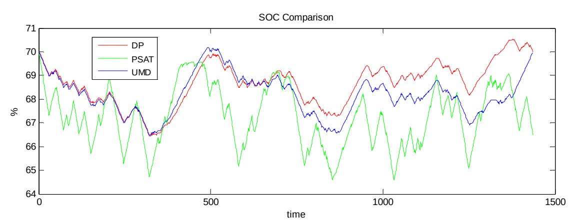
and LA 92 drive cycles, the ***IPC*** gives almost identical fuel consumption as the optimal (DP) controller. On the UNIF01 drive cycle, the ***IPC*** saved 2.68% fuel in comparison to software tool's own controller [14]. Clearly by combining a prediction of the roadway type and congestion level with the power management strategy, we were able to realize a fuel economy improvement over the existing conventional strategy.




(a) SOC compensation during driving cycle UDDS




(b) SOC compensation during driving cycle UNIF01




(c) SOC compensation during driving cycle LA92

Figure 5. SOC comparison on three driving cycles. The X axis represents time measured in seconds and the vertical represents the SOC measured in percentages.

## V. CONCLUSION

We have presented a neural network designed and developed for in-vehicle prediction of 11 different roadway types and traffic congestion levels. We presented the features and feature extraction algorithm we developed for the neural network. We also described the importance of the two parameters, $\Delta w$, the signal window size, and $\Delta t$, the prediction step, on the accuracy of prediction results. Our simulation results using the ***IPC*** intelligent controller show that vehicle fuel consumption can be improved through the use of drive cycle and congestion level prediction. Currently we are applying the roadway prediction knowledge to a hybrid vehicle power management system. We anticipate more significant fuel reduction will be achieved in hybrid vehicle power systems.

TABLE III

PERFORMANCE COMPARISON ON FUEL CONSUMPTION

| | Algorithm | Fuel Consumption (gram) | **Final SOC (%)** | Fuel Consumption After SOC correction 70% (gram) | **Saving From software controller [14]** |
|---|---|---|---|---|---|
| UDDS | **software controller [14]** | 701.1821 | 65.32% | 712.5429 | |
| | Off Line DP (optimal) | 700.2153 | 70.00% | 700.2153 | 1.7301% |
| | ***IPC*** | 700.1142 | 69.96% | 700.2207 | 1.7293% |
| ***UNIF01*** | **software controller [14]** | 1269.225 | 55.37% | 1304.799 | |
| | Off Line DP (optimal) | 1268.153 | 70.00% | 1268.153 | 2.8085% |
| | ***IPC*** | 1269.637 | 69.96% | 1269.743 | 2.6866% |
| **LA92** | **software controller [14]** | 980.191 | 66.56% | 988.63 | |
| | Off Line DP (optimal) | 973.428 | 70.00% | 973.42 | 1.538% |
| | ***IPC*** | 973.3181 | 69.96% | 973.42 | 1.538% |

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